Modified Fuzzy-Anisotropic Gaussian Kernel and CRB in Denoising SAR Image

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DECLARATION

I certify that,

a. The work presented in this thesis is an original content of the research done by myself under the general supervision of my supervisor.
b. The work has not been submitted to any other institute for any degree or diploma.
c. The data used in this work is taken from free source and its credit has been cited in reference.
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e. I have followed the thesis guidelines provided by the institution

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CERTIFICATE

This is to certify that the work done in the report entitled "**Modified Fuzzy-Anisotropic Gaussian Kernel and CRB in Denoising SAR Image"** by "**Sandula Pavan"** is a record of research work carried out by him in National Institute of Technology, Rourkela under my supervision and guidance during 2014-15 in partial fulfillment of the requirement for the award of degree in Master of Technology in Electronics and Communication Engineering (Signal and Image Processing), National Institute of Technology, Rourkela. To the best of my knowledge, this thesis has not been submitted for any degree or diploma.

Dr. Lakshi Prosad Roy
Asst. Professor

DEDICATED

To

My Parents

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ABSTRACT

Radar speckle noise is often modeled as multiplicative noise for such that higher the intensity higher the speckle noise. As a result, the brighter pixel values are having more noise. The presence of speckle not only complicates visual image interpretation but also the classification of automated image is difficult in corrupted SAR image. Therefore, speckle has to be reduced before analyzing the SAR image.

Thus, speckle is the main problem (mingled) in Synthetic Aperture Radar (SAR) images. Speckle is existed due to constructive and destructive interference of coherent signal. In order to reduce it, we approach enhanced kernel based filter. Till there are so many techniques are developed to remove speckle content in SAR system. But no proper technique as been developed to remove speckle content completely. In our project MMSE based filter technique is used. We propose a new integrated Fuzzy Anisotropic Gaussian Kernel (FAGK) for denoising Synthetic Aperture Radar (SAR) Images. Here, texture information lies on principal orientation should be multiplied with fuzzy membership function through the anisotropic Gaussian kernel. It presents Cramer-Rao Bound (CRB) which can be estimated by taking ensemble of texture modeled covariance matrix for different denoising methods. Later, CRB can be found for an index of speckle suppression. Thus, developed filter gives good result in preservation of texture and in structure enhancement. It also presents evaluation of speckle suppression ability, where an index named SMPI (Speckle Suppression and Mean Preservation Index). It compares CRB for the evaluation of SMPI index with different denoising methods.

contents

ABBREVIATIONS

AGK	: Anisotropic Gaussian Kernel
CRB	: Cramer-Rao Bound
FAGK	: Fuzzy Anisotropic Gaussian Kernel
MMSE	: Minimum Mean Square Error
SAR	: Synthetic Aperture Radar
SMPI	: Speckle Suppression and Mean Preservation Index
SSI	: Speckle Suppression index

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CHAPTER 1

introduction

1. Introduction

Now-a-days, SAR is widely used and gets much more significance due to its capability of operating in day and night, in all weather conditions, providing high resolution images and etc. However, the quality of SAR images is degraded due to coherent speckle noise. Indeed, many filtering techniques are developed to extract texture and to remove speckle noise. Despeckling techniques put an emphasis on texture and structure preservation and obviously to remove speckle content. Basically, there are two approaches of filters for despeckling namely, parametric and non-parametric. The known filters as Lee filter [6], Frost Filter [7], Kaun Filter [8] are examples of non-parametric filters. Parametric model depends on various distributions and their parameters to fit the data.

In this thesis, a new integrated Fuzzy-AGK (FAGK) was developed to filter the SAR images and considering statistics of autocovariance function which is locally approximated by two-dimensional Anisotropic Gaussian Kernel to signify texture by its local orientation and anisotropy. A parametric form of two dimensional autocovariance is manifested by Gradient Structure Tensor is locally approximated by Anisotropic Gaussian Kernel (AGK) to get the notion of anisotropy and local orientation [2].The AGK Filtering method is failed in proper edge preservation in texture so with this, a novel Fuzzy logic kernel is implemented to preserve the edges properly in texture information. Thus, an integrated Fuzzy AGK MMSE filter is developed by simple kernel multiplication of both. Here fuzzy membership function is defined in [4]. In this thesis we enhanced fuzzy membership function by using mean of gradient difference between central and neighborhood pixel for further development as proposed. Then find CRB for SMPI parameter. Firstly, it is estimated by finding ensemble of different autocovariance of relevant Texture information as a fisher information matrix

So far many despeckling filters had been developed. Still there is no proper method to evaluate a texture eliminating speckle content totally. Every method has its advantage and disadvantage. So we sought to introduce an integrated kernel which is for edge and structure enhancement. Anisotropic Gaussian Kernel (AGK) is discussed in [2]. This method of denoising is failed in proper edge preserving. In particular it leads to sharp edges causing artifacts. Fuzzy logic is discussed in [3]. Here square of logarithmic difference between central and neighborhood pixels is considered. Because of the noise content, larger is the difference in mean power and intensity within homogeneous areas.

A new fuzzy Gaussian membership function is introduced. Here this membership function is chosen because AGK follows Gaussian so kernel which is going to scale it also should follow Gaussian.

This fuzzy Gaussian membership function deals with proper edge preservation. After establishing kernel, it has to be integrated with AGK. Finally it concludes with a mean preservation and speckle suppression index named as SMPI.

For this index, a Cramer-Rao Bound (CRB) has been calculated taking different denoising images of same. Here the second order statistics of autocovariance matrices of different denoising images and their ensemble are considered in calculating fisher information matrix. Finally CRB for SMPI index is found.

1.1 Motivation

SAR has advantage and ability to capture image in day and night and in all weather conditions. It gives high resolution images without depending upon distance from it measured. It also gives information about snow wetness, soil moisture etc.

However, speckle is the main problem in SAR imaging system. So many filtering techniques had been developed. In this direction, the research work is going.

No proper method had been developed till. This Thesis shows CRB for speckle suppression and mean preservation index in order to find how much extent the speckle can be removed.

1.2 Objective

The main objective of this work is to introduce a new fuzzy membership function such that it reduces the effect of sharp edges. Here so many methods have been developed but no method is comparable to each other. Each method has its own advantage and disadvantage. For this CRB for speckle suppression and mean preservation index is found. The proposed filter will compare the results with other techniques of filtering and showing better.

1.3 Thesis Outline

This Thesis is organized into 5 chapters. The first chapter speaks about introduction of SAR imaging system and its associated problems of noise and the literatures deal with different kernel for denoising. The second chapter deals with spatial texture model and coefficient of variation and gives a brief discussion about AGK and its flowchart. The third chapter signifies the fuzzy logic and its frame work. The forth chapter deals with other filtering techniques. The fifth chapter deals with proposed filter, it's finding weighted statistics and implementing Lee MMSE filter and gives description about CRB for SMPI parameter in finding out for a SAR image with experimental results, conclusion and future work. Finally bibliography is given.

CHAPTER 2

spatial texture model

2. Spatial Texture Model

2.1 Product Model

In this context single-look data is considered only, because while considering average spatially there is loss in information. It is well described that speckle noise follows multiplicative noise. The observed intensity I of SAR image can be written as follows:

$$I_{i,j} = T_{i,j} F_{i,j} \quad (1)$$

where $I_{i,j}$ is the observed intensity at each pixel value, $T_{i,j}$ is the texture intensity at each pixel value ,and $F_{i,j}$ is the speckle content at each pixel

A. Single-point statistics of SAR intensity

Single-point statistics are the most common statistical descriptors of SAR intensity. It has been shown in the [2] that the variance of texture σ_T^2 can be obtained in the following equation.

$$\sigma_T^2 = \frac{CV_I^2 - \sigma_F^2}{1 + \sigma_F^2} \quad (2)$$

where, CV_I can be described for SAR image in following sessions and variance of speckle is σ_F^2 which should be one for single-look data.

B. Two-point statistics

Actually the model used to describe about two-point statistics of SAR intensity, and it is presented to have more complete description of the SAR texture. A parametric form for two-dimensional (2-D) autocovariance function is used to study notion of local orientation and spatial anisotropy since it is regarded as indicator of spatial correlation. Therefore this model deals with the deterministic structures and the correlation of heterogeneous clutter spatially. Thus spatial information imparted in two-point statistics, intensity can be characterized by parametric form through defining autocovariance

$$C_I(\tau) = R_I(\tau) - \mu_I^2 \tag{3}$$

where $R_I(\tau) = E[I(t+\tau)I(t)]$ is the autocorrelation of the observed image and τ represents 2D spatial location.

2.2 Coefficient of Variation

In probability theory and statistics the coefficient of variation is standard measure for dispersion in probability distribution or frequency distribution.

It is defined as the ratio of standard deviation to mean, it can take only positive values.

$$CV = \frac{\sigma}{\mu} \tag{4}$$

where σ is standard deviation and μ is the mean of Image

The advantage of coefficient of variation is, it considers the data with respect to mean. So for comparison between different sets of data it might be useful.

In the analogy of image especially SAR images, based on threshold with the median value different zones have been categorized within homogeneous areas namely

1. high variability
2. low variability
3. very low variability.

A better interpretation of results is obtained by distinguishing different zones.

2.3 Estimation of Texture Parameters

A. Gradient Structure tensor:

It is already mentioned that second order statistics cannot be applied directly in denoising SAR image due to presence of speckle. So smoothed image is considered by applying Gaussian kernel. Thus noise free scene at scale σ can be approximated by $I_\sigma = K_\sigma * I$, where K_σ is isotropic Gaussian kernel with standard deviation σ and the symbol * is convolution operator. This representation guarantees that the image differentiability and operator GST [3] may then be introduced as follows

$$J = K_\rho * \left(\nabla I_\sigma \nabla I_\sigma^T\right) \tag{5}$$

where, ∇ is the 2-D gradient operator. The Gaussian kernel K_ρ is a spatial averaging window that gives an idea about the mathematical expectation.

Thus, the AGK model with covariance matrix Σ for the second-order statistics of I_σ, it is possible that evaluating this matrix gives the correlation lengths at scale,

$$J = 2\sigma_{I_\sigma} \Sigma^{-1} \tag{6}$$

B. Extracting the descriptive parameters:

Compute the eigendecomposition of the GST as shown in [4]. Without computing the autocorrelation function (ACF) it is possible to estimate the parameters of the model. The correlation lengths can get back from the eigenvalues λ_1, λ_2 of J. The dominant orientation is then determined by eigenvector k_2, has maximum correlation length, and its corresponding angle is

$$\theta = \tan^{-1}\left(\frac{k_{2,y}}{k_{2,x}}\right) \tag{7}$$

The gradient response magnitude is usually named “orientational energy” and is expressed as

$$E = \lambda_1 + \lambda_2 \tag{8}$$

To quantify the importance of the principal orientation, it is useful to define a descriptor named spatial anisotropy as

$$A = 1 - \frac{\lambda_2}{\lambda_1} \tag{9}$$

2.4 Introducing AGK and its significance:

In this section, an anisotropic Gaussian kernel is established. It is enhancement of the minimum mean square error (MMSE) filter that is found in the present local texture model.

Within a window, speckle adaptive filtering techniques are depend upon local statistics estimation which surrounds the central pixel. local statistics estimation of fixed square window is the main limitation. The problem is, if edges or structures are exist within the window, local statistics are not to be remained stationary and the poor estimation by a uniform spatial averaging. But the information of anisotropy is to compute a weighted local statistics with stronger weights given to pixels that orient in principal direction given in [2]. This was depicted in a following flow chart. Firstly the spatial parameters are estimated by calculating Gradient structure tensor of an image, then decompose its eigen values and eigen vectors. Thus, orientation angle and anisotropy are obtained by using above equations. These parameters indicate that for each pixel of original image the weighted statistics are given according to stronger weights to pixel that lie in the direction of its orientation angle

$$W(d) = \frac{1}{K} \exp\left(-d^T \Sigma_{\hat{A},\hat{\theta}}^{-1} d\right) \tag{10}$$

where, K is a normalization constant that ensures that the sum of the weights equal to 1, i.e.,

$$\int_{u \in R^2} W(u)\, du = 1 \tag{11}$$

The covariance matrix of this anisotropic Gaussian filter is given by

$$\Sigma_{\hat{A},\hat{\theta}} = R_{\hat{\theta}}^{T} \begin{bmatrix} \rho^{2} & 0 \\ 0 & \rho^{2}\left(1-\hat{A}\right) \end{bmatrix} R_{\hat{\theta}} \tag{12}$$

where, the rotation matrix $R_{\hat{\theta}}$ with angle $\hat{\theta}$. ρ of the Gaussian window K_{ρ} is the limited scale of standard deviations of this kernel are

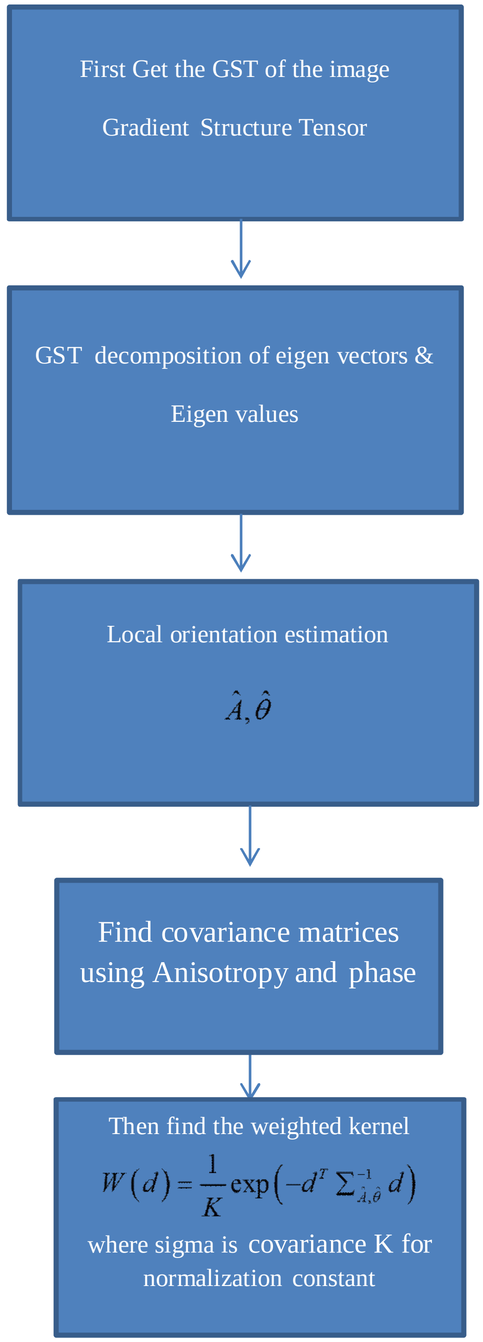


Fig 2.1 Shows the formation weighted anisotropic Gaussian kernel

Thus anisotropic Gaussian kernel is established which is briefly described in [1] & [2]. Here we shows the main theme of finding anisotropic Gaussian kernel.

CHAPTER 3

fuzzy framework

3. Fuzzy Frame work

3.1 Introduction of Fuzzy Logic:

In Image Processing Fuzzy Technique are applied in certain applications like intensity transformation and spatial filtering. Fuzzy sets provide a framework for incorporating certain distribution in solving problems by a human knowledge.

3.2 Fuzzy sets:

A set is a collection of objects (elements) and set theory explains the operation of on and among sets. Set theory along with mathematical logic is the foundation of classical mathematics. Using the knowledge of set theory the membership function is developed. Let Z denotes set of all people and to define a subset which is set of young people can be defined as A. In order to form subset we need to define a membership function such that it can assign a value 1 or 0 to every element. Since we are discussing about bi-valued logic, the membership function simply defines a threshold at or below considering one-logic and above another-logic. If you need more flexibility in what mean an idea of logic, that is gradual transition from one to other logic.

Thus membership functions play a major in degree of transition from one-logic to another-logic.

3.3 Membership functions:

Triangular:

$$\mu(z) = \begin{cases} 1-(a-z)/b & a\text{-}b \le z < a \\ 1-(z-a)/c & a \le z \le a+c \\ 0 & \text{o.w} \end{cases}$$

Trapezoidal

$$\mu(z) = \begin{cases} 1-(a-z)/c & a\text{-}c \le z<a \\ 1 & a \le z<b \\ 1-(z-b)/d & b \le z \le b\text{+}d \\ 0 & \text{o.w} \end{cases}$$

Sigma:

$$\mu(z) = \begin{cases} 1-(a-z)/b & a\text{-}b \le z<a \\ 1 & z>a \\ 0 & \text{o.w} \end{cases}$$

Gaussian:

$$\mu(z) = \begin{cases} \exp-\dfrac{(z-a)^2}{2b^2} & a\text{-}c \le z \le a\text{+}c \\ 0 & \text{o.w} \end{cases}$$

S-shape:

$$S(z;a,b,c) = \begin{cases} 0 & z<a \\ 2\left(\dfrac{z-a}{b-a}\right)^2 & a \le z \le b \\ 1\text{-}2\left(\dfrac{z-c}{b-c}\right)^2 & b<z \le c \\ 1 & z>c \end{cases}$$

Bell –shaped :

$$\mu(z) = \begin{cases} S(z;c-b,c-b/2,c) & z \le c \\ 1\text{-}S(z;c,c+b/2,c+b) & z>c \end{cases}$$

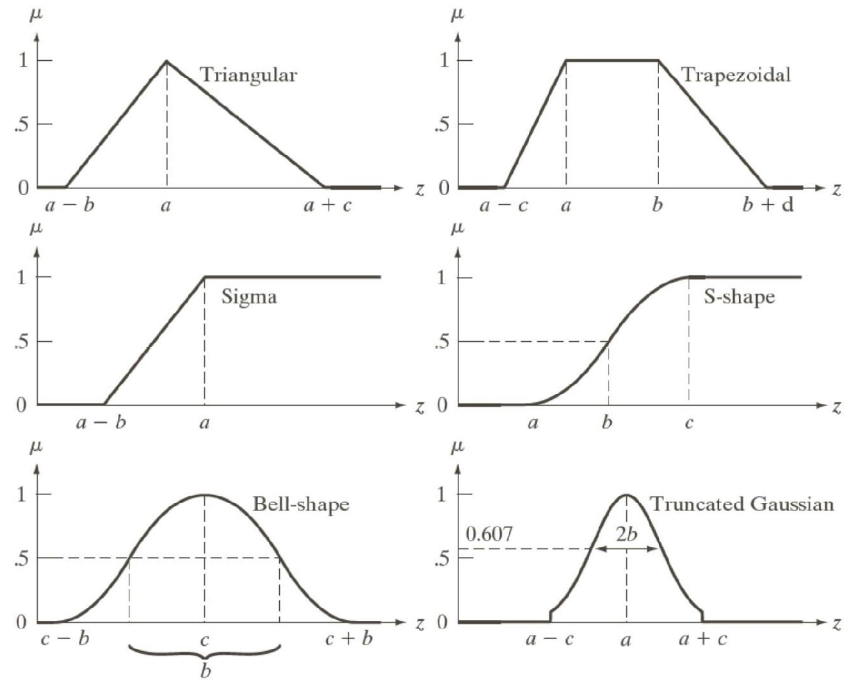


Fig 3.1 Showing different membership functions

In the next, we introduce Fuzzy window compared to the edge aligned window. Then providing fuzzy membership function we will derive fuzzy filtered technique of denoising SAR images.

3.4 Edge-aligned window vs. Fuzzy window:

Edge –aligned window operation is a common approach to preserve edges in denoising. Here portion of pixel in neighborhood window is taken into account, while we consider filtering. This type of edge-aligned-window may lead to several problems. For example to cover the same scattering-mechanism pixels the distribution of texture is always too complex for a simple shape window. Each pixel in the fuzzy window is shown in fig.2, and is assigned a membership function value ranging from 0 to 1. One can easily see that the fuzzy window is the special form of edge aligned window, where inside the window the pixel take membership function value as 1, outside the window the pixel take as 0.

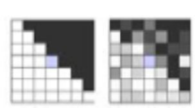


Fig 3.2 Fuzzy window (right) vs. edge-aligned-window (left)

3.5 Definition of Fuzzy membership function:

The central pixel (the pixel to be filtered) in the fuzzy window is denoted as (i, j), the neighborhood pixel as $(i+m, j+n)$, and the value of fuzzy membership is denoted as $w_{(i,j)}^{(m,n)}$. $w_{(i,j)}^{(m,n)}$ measures the possibility that the two pixels (i, j) and $(i+m, j+n)$, and belongingness of the same scattering mechanism. Given a SAR image with its power intensity denoted as I, we would like to define the membership function based on the intensity value. The membership function value $w_{(i,j)}^{(m,n)}$ is given as

$$w_{(i,j)}^{(m,n)} = \exp\left(-\beta \log^2\left(\frac{1+I_{i,j}}{1+I_{i+m,j+n}}\right)\right) \tag{1}$$

where $I_{i,j}$ and $I_{i+m,j+n}$ denote the intensity values of pixel (i, j) and $(i+m, j+n)$, respectively; β is a constant parameter. One can easily understood that the smaller contrast between the two pixels is, the closer $w_{(i,j)}^{(m,n)}$ reaches to 1, which infers the two pixels belong to the same scattering mechanism.

Next, we propose a new kernel named as Fuzzy-anisotropic Gaussian kernel, it is manipulated by multiplying fuzzy window and anisotropic gaussian kernel with same dimensions. It is given as follows:

$$q_{(i,j)}^{(m,n)} = w(d) \times w_{(i,j)}^{(m,n)} \tag{2}$$

where $w(d)$ is defined earlier as anisotropy gaussian window and, $w_{(i,j)}^{(m,n)}$ is a value of fuzzy membership.

For our filter, we need to estimate the local statistics from each filtered pixel's local window, which hints that the choice of this window is important for the performance of filter. Henceforth, we propose a fuzzy window along with, anisotropy gaussian window where, it gives stronger weights to the pixel that orient in the direction of orientation principally. Our approach is described in the following and a block diagram of its steps is drawn in Fig. 2.

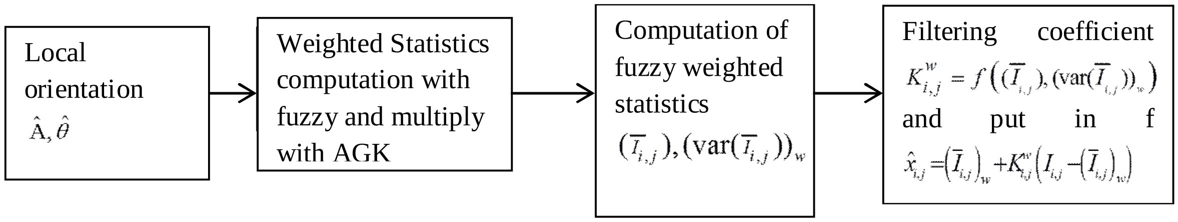


Fig 3.3 Main steps of our integrated filtering technique

CHAPTER 4

other filtering techniques

4. Other Filtering Techniques

4.1 Introduction

Basically to study any image and its characteristics we need to process the SAR image. In such processing denoising is one. For this, so many filtering techniques have been developed. In such many we are discussing now. Some filtering techniques are:

(1)Median Filter

(2)Boxcar

(3)Lee

(4)Kaun

(5)Frost

(6)Enhanced Lee

(7)Enhanced Frost

(8)Gamma MAP (maximum a posterior)

4.2 Filtering Techniques:

(1) Median Filter:

This Filter is a non-linear type. It is derived from the principle of MLE (Maximum Likelihood Estimation) by considering the signal to be contaminated by additive noise which follows Laplacian distribution. In some cases it is more efficient than most other filters.

$$\hat{I} = Median_{\substack{|x|<|x_o|,\\ |y|<|y_o|}} \left(I\left(x, y\right) \right) \tag{1}$$

(2)Boxcar Filter:

It is considered as local mean of the image. While considering local mean there is a loss in texture information due to change in spatial resolution. Even though it is denoising greatly the texture information is lost in this scenario.

$$\hat{I} = \overline{I} \tag{2}$$

(3)Lee Filter:

Here method of local statistics is introduced by criteria of Minimum Mean Square Error (MMSE). It reduces speckle noise while preserving edges in the image

$$\hat{I} = I.W + \overline{I}\left(1 - W\right) \tag{3}$$

where $$W\left(x, y\right) = 1 - \frac{C_{si}^2}{C_I\left(x, y\right)}$$

where C_{si} - standard speckle index C_I is varied standard speckle index.

$$C_{si} = \frac{\sigma}{\mu}$$

where σ is local standard deviation of image and μ is the mean of the image

Standard speckle index is introduced as

$$C_{si} = \frac{0.523}{\sqrt{N}}$$

N is the number of looks.

In our case is N=1

*Note: $\overline{I}$ is the local mean of image, I is the observed image and $\hat{I}$ is the filtered image

(4) Kaun filter:

It is derived from MMSE criteria making an assumption of a non-stationary variance C. It is slightly better than the Lee filter due to the fact of approximation is not required in the total derivation.

$$\hat{I} = I.W + \overline{I}\left(1 - W\right) \tag{4}$$

where $$W\left(x, y\right) = \frac{1 - C_{si}^{2} / C_{I}\left(x, y\right)}{1 + C_{si}^{2}}$$

(5) Frost Filter:

Here also the principal involved is MMSE. The local statistics of image can be varied by filter kernel and so it can reduce the noise and can keep the edges.

$$\hat{I} = I * W \tag{5}$$

where $$W\left(x, y\right) = K_{1} e^{-k_{d} C_{I}\left(x, y\right)\sqrt{x^{2} + y^{2}}}$$

where k_d is a damping factor less than 1

(6)Enhanced Lee Filter:

Based on Lee filter A.Lopes improved the ability to preserve edges in the image by modifying Lee filter

$$\begin{aligned} \hat{I} &= \overline{I} && C_{I} \le C_{si} \\ \hat{I} &= I.W + \overline{I}\left(1 - W\right) && C_{si} < C_{I} < C_{\max} \\ \hat{I} &= \overline{I} && C_{I} \ge C_{\max} \end{aligned} \tag{6}$$

where $$W\left(x, y\right) = -k_{d} \frac{C_{I}\left(x, y\right) - C_{si}}{C_{\max} - C_{I}\left(x, y\right)}$$

(7)Enhanced Frost Filter:

The similar kind of modification which Lee had done in Lee filter, Frost modified and introduces Enhanced Frost Filter.

$$\begin{aligned} \hat{I} &= \overline{I} && C_I \le C_{si} \\ \hat{I} &= I * W && C_{si} < C_I < C_{\max} \\ \hat{I} &= \overline{I} && C_I \ge C_{\max} \end{aligned} \tag{7}$$

where $$W(x,y) = -k_d \frac{C_I(x,y) - C_{si}}{C_{\max} - C_I(x,y)} \sqrt{x^2 + y^2}$$

(8)Gamma MAP:

It is developed under assumption that image follows Gamma distribution and which believed more suitable for realistic case

$$\begin{aligned} \hat{I} &= \overline{I} && C_I \le C_{si} \\ \hat{I} &= \frac{\overline{I}.K + \sqrt{\overline{I}^2 K^2 + 4\alpha N \overline{I}}}{2\alpha} && C_{si} < C_I < C_{\max} \\ \hat{I} &= \overline{I} && C_I \ge C_{\max} \end{aligned} \tag{8}$$

where $$K = \alpha - N - 1$$

and $$\alpha = \frac{1 + C_{si}}{C_I^2 - C_{si}^2}$$

CHAPTER 5

proposed filter

5. Proposed filter

5.1 Background

In AGK Lee MMSE filter; the main disadvantage is proper edge preservation. Secondly, AGK follows Gaussian distribution. So the integrated kernel which is supposed to enhance AGK should also follow Gaussian distribution. Fuzzy logic is implemented by Gaussian membership function for proper edge preservation. In finding out boosted edge factor, the noise free image is considered by taking local mean of the image. Then, Laplacian window is considered according to the coefficient of variation index to get finer details i.e., if it is higher, larger size of window will be considered or vice versa. Applying preferred window size of Laplacian, it should be scaled down by a factor of window size. Because of that, while getting difference between them; the boosted edginess will be accumulated. In particular square of the logarithmic difference should be considered as discussed in [4]. In order to resolve our problem, certainly a new introduced metrics named as coefficient of boosted edginess of defined window is considered. Then it is defined with respect to mean for getting proper proportion. But it didn't have proper scaling factor due to difference between Laplacian image and its scaled image. So considering scaling factor, the whole thing is introduced into negative exponential of fuzzy Gaussian membership function such that it can compensate the boosted edge.

5.2The frame work of new Fuzzy membership function

(1) Consider pre-defined Laplacian image as A, and then scale it

$$B(i, j) = (1/9) \cdot A(i, j) \tag{1}$$

(2) Consider the central pixel as (i, j), and the neighborhood pixel as $(i+m, j+n)$ then square of the logarithmic difference between the $A(i, j)$ and $B(i+m, j+n)$, where 0< m, n <4.

$$w_{i,j}^{m,n} = \left(\log\left(\frac{1+A(i,j)}{1+B(i+m,j+n)} \right) \right)^2 \tag{2}$$

(3) Mean of $w_{i,j}^{m,n}$ is defined as:

$$C = (1/9) \cdot sum(w) \tag{3}$$

(4) Consider normalized exponential term as follows

$$K_{i,j}^{m,n} = \frac{1}{M} \exp\left(-\beta \cdot \left(\frac{w_{i,j}^{m,n}}{C} \right)^2 \right) \tag{4}$$

For Coefficient of variation CV $= \frac{\sigma}{\mu}$, CV<1

$$K_{i,j}^{m,n} = \frac{1}{M} \exp\left(-\beta \cdot \left(\frac{w_{i,j}^{m,n}}{C} \right)^4 \right) \tag{5}$$

For CV>1, where, M is normalization constant.

where, β can be calculated as

$$\beta = \frac{1}{2} \{ \max(\varepsilon) + \min(\varepsilon) \} \tag{6}$$

where, ε is defined as

$$\varepsilon = \frac{9 \cdot (w/C)^2 - \sum_{i=1}^{9} (w_i/C)^2}{\sum_{i=1}^{9} (w_i/C)^2 \left((w/C)^2 - \sum_{i=1}^{9} (w_i/C)^2 \right)} \tag{7}$$

So ε is 3×3 matrix .In order to get the scalar constant we will use mid order statistics.

β gives the ordered statistics parameter to concordant according to the edge factor in original image. β is scaling factor

The scaling factor is considered, such that whole membership function attains minimum. It is observed that if it is raised to higher exponential for some other purposes, the scaling factor will not depend upon it. The scaling factor becomes negligible while considering higher order membership function to resolve β. For this reason, the scaling factor was chosen from its lower order membership function.

5.3 Kernel Integration:

The product of proposed kernel and AGK kernel with same window size is defined as follows

$$q_{i,j}^{m,n} = K_{i,j}^{m,n} \times W(d) \tag{8}$$

Totally can be depicted in following flowchart:

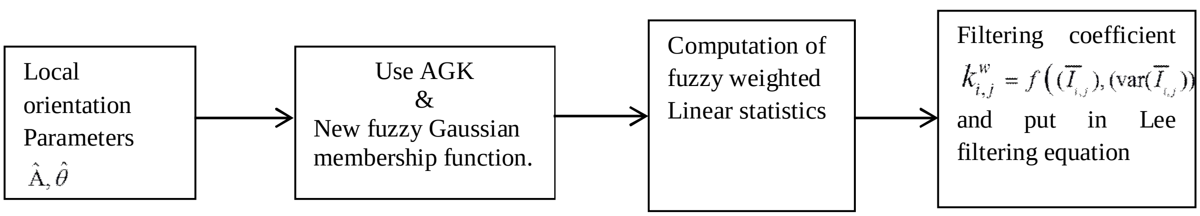


Fig. 5.1 Showing steps involved in proposed filter

5.4 WEIGHTED STATISTICS IN LINEAR MMSE FILTER

In case of MMSE filtering the local weighted mean and variance are computed as follows:

$$\left(\overline{I}_{i,j}\right)_w = \sum_{m=-1}^{1} \sum_{n=-1}^{1} q_{i,j}^{m,n} \cdot I_{i+m,j+n} \tag{9}$$

$$\left(\mathrm{var}\left(\overline{I}_{i,j}\right)\right)_w = \sum_{m=-1}^{1} \sum_{n=-1}^{1} q_{i,j}^{m,n} \cdot \left(I_{i+m,j+n} - \left(\overline{I}_{i,j}\right)_w\right)^2 \tag{10}$$

where, $\left(\overline{I}_{i,j}\right)_w$ is the weighted mean and $\left(\mathrm{var}\left(\overline{I}_{i,j}\right)\right)_w$ is the weighted variance.

In next step we calculate the filtering coefficient $k_{i,j}^{w}$ having a value between 0 and 1. This parameter adjusts the tradeoff between the intensity values of observed image and its local mean. Thus this is defined as follows:

$$k_{i,j}^{w} = \frac{\left(\mathrm{var}\left(\overline{I}_{i,j}\right)\right)_{w} - \left(\overline{I}_{i,j}\right)_{w}^{2}\sigma_{v}^{2}}{\left(1+\sigma_{v}^{2}\right)\left(\mathrm{var}\left(\overline{I}_{i,j}\right)\right)_{w}} \tag{11}$$

where, σ_{v}^{2} is variance of noise taken as 1.

Then we use (15) in modifying existing Lee filtering equation

$$\hat{x}_{i,j} = (\overline{I}_{i,j})_{w} + k_{i,j}^{w}\left(I_{i,j} - \left(\overline{I}_{i,j}\right)_{w}\right) \tag{12}$$

5.5 CRB in Estimation:

The CRB for parameter estimation can be found from Fisher Information Matrix. In order to find Fisher Information Matrix it is necessary to estimate autocovariance matrix. It is observed that at zero lag of finding covariance there is contribution of speckle and in elsewhere its contribution is very less. However, we cannot consider autocovariance of texture directly. As texture and speckle are assumed to be statistically independent it explains autocorrelation of texture and observed image. From that it is discussed that the covariance of texture and observed image is interrelated in [1] Thus a direct relationship between the autocovariances of observed image and texture C_I and C_T respectively is given in following. Then to find fisher information matrix we need to ensemble the covariance matrices of same observed image. For that, different denoising filters of covariance matrices are chosen. In this thesis five different denoising techniques of same image is considered.

$$C_T = \frac{1}{N}\sum_{q=1}^{N} C_{Tq} \tag{13}$$

where, N is the Number of different denoising techniques of same image. As N increases the estimation of texture covariance matrix is better.

and, $$C_{T_q} = \frac{\frac{C_I(0,0)}{\mu_I^2} - \frac{1}{L}}{1+\frac{1}{L}} \tag{14}$$

where, L indicates Number of looks and μ_I is denoted as absolute mean of the observed image.

$$I^{-1}(\theta) = C_T \tag{15}$$

where, $I(\theta)$ is a Fisher Information Matrix.

$$CRB = \frac{\partial g}{\partial \theta} \cdot I^{-1}(\theta) \cdot \left(\frac{\partial g}{\partial \theta}\right)^T \tag{16}$$

where $\frac{\partial g}{\partial \theta}$ is a Jacobian matrix.

In order to find for a parameter a Jacobian matrix of size 1×2 matrix, which is defined as

$$\frac{\partial g}{\partial \theta} = \left[-(I_v)/(I_{mv}) \quad -\left(\left(1+(I_{mm}-I_m)\right)*I_v\right)/\left((I_{mv})^2\right) \right] \tag{17}$$

Variance of noisy Image= I_{mv}

Mean of noisy Image= I_{mm}

Mean of Filtered Image= I_m

Variance of filtered Image= I_v

θ is [I_{mm} I_{mv}]

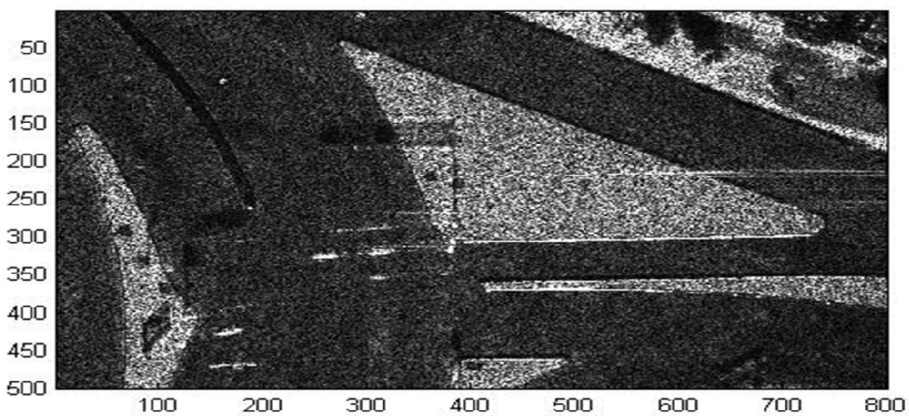
5.6 Results and Discussion

We have shown different filtering techniques and CRB for our denoised image for SAR images with different CV

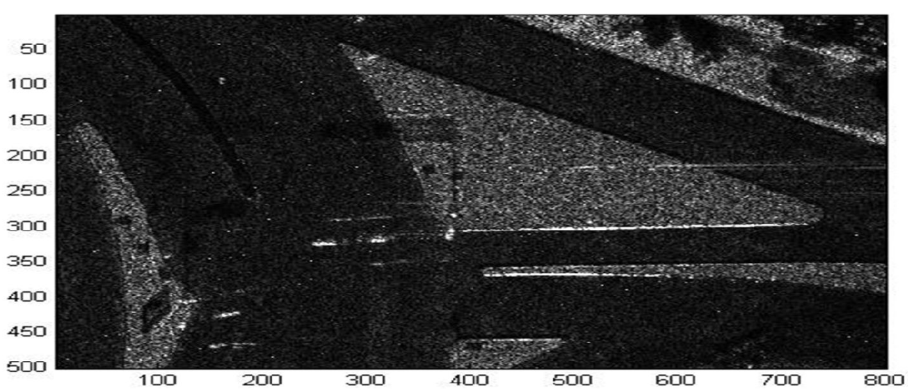
TABLE 5.1

Results of showing different filter techniques

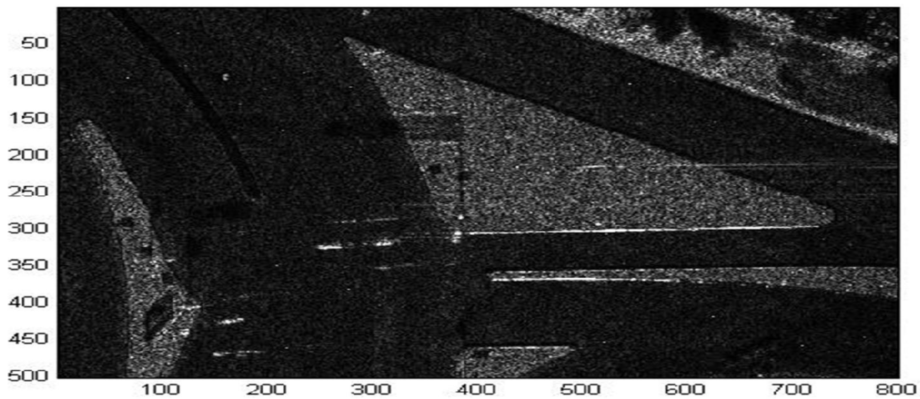
Images (CV)	SMPI PARAMETER				CRB
	AGK	0.1181	Fuzzy AGK (Proposed-1)	Proposed-2	
SAR a (0.5144)	0.8324	0.1270	0.5002	0.4999	0.1181
SAR b (2.6336)	0.5746	0.1269	0.4980	0.4972	0.1270
SAR c (0.2389)	0.8098	0.1281	0.5007	0.4989	0.1269
SAR d (1.3171)	0.6300	0.5298	0.5016	0.5009	0.1281



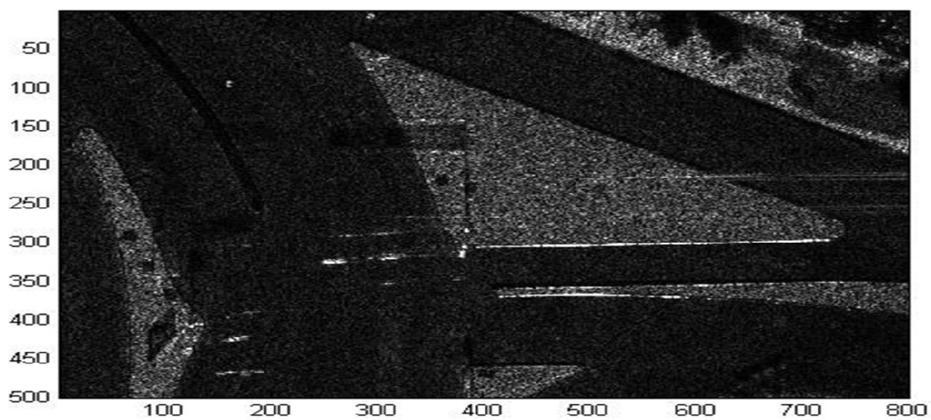
(a)



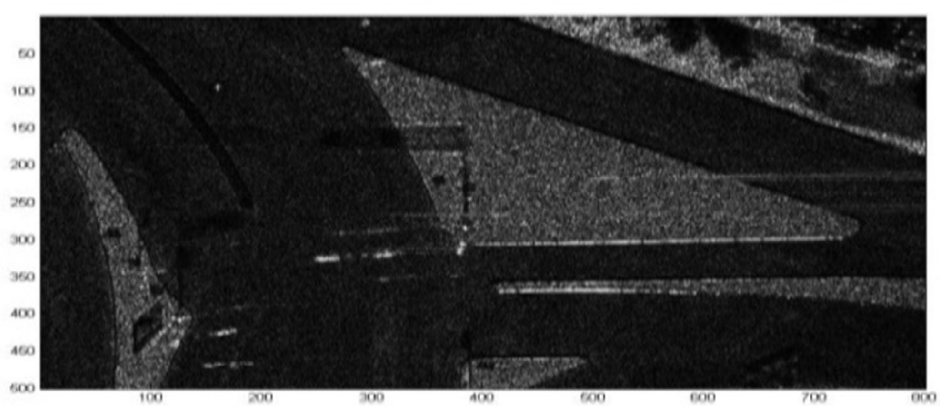
(b)



(c)



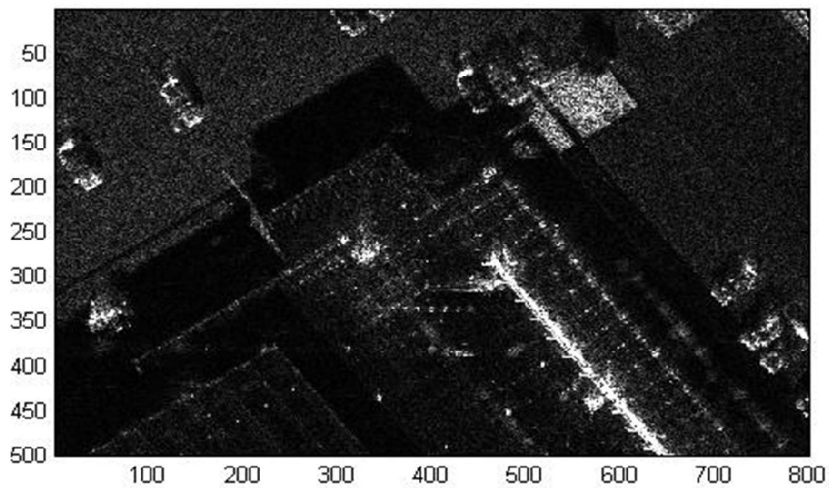
(d)



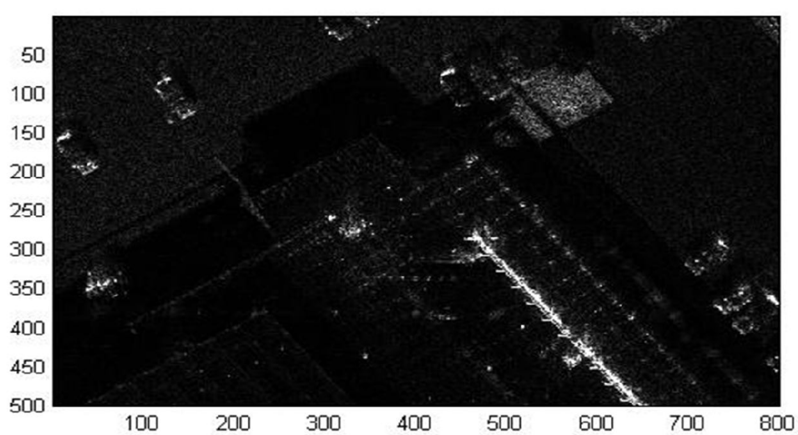
(e)

Fig. 5.2(a)Original noisy Image (b)AGK filter (c)Fuzzy filter (d)Fuzzy AGK (Proposed-1) (e)Proposed filter-2

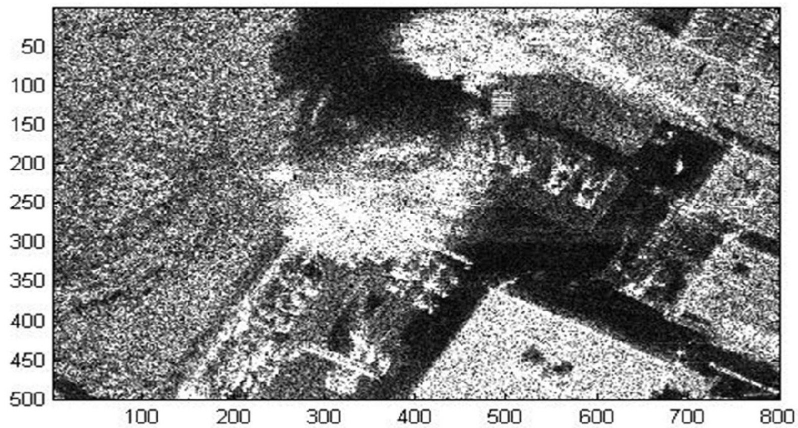
For different values of CV different set of Images are showed



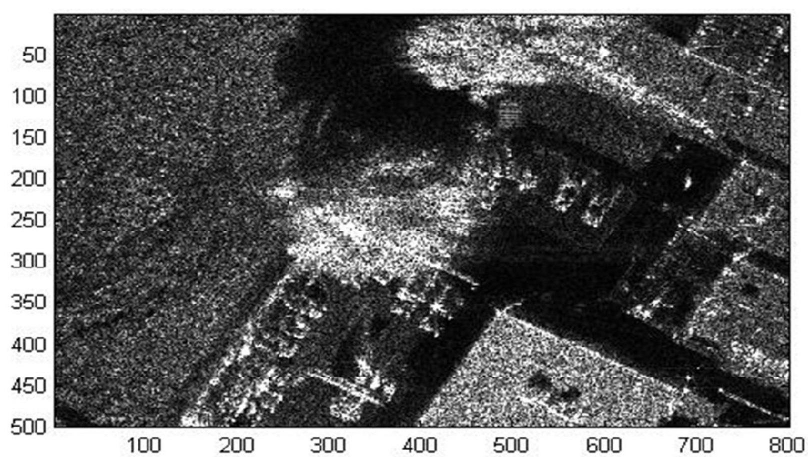
(a)



(b)

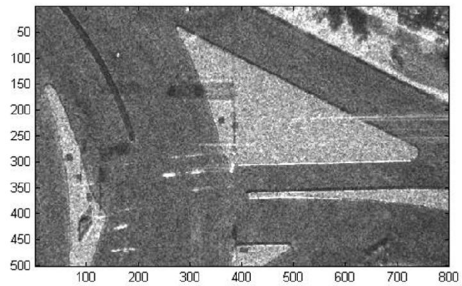


(c)

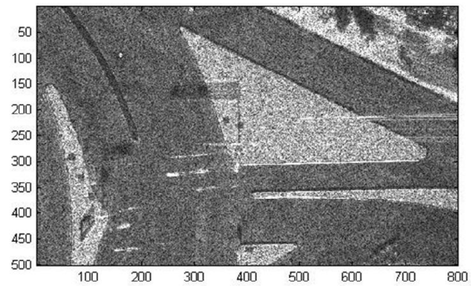


(d)

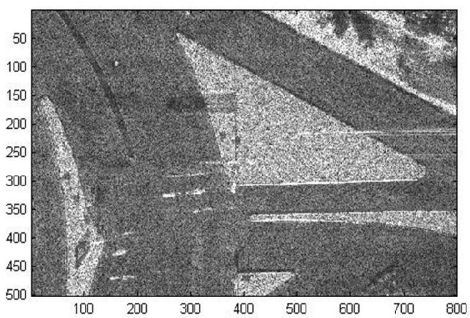
Fig. 5.3(a) original noisy Image for CV>2 (b) Proposed filter whose window size is 5×5 to get finer details (c) original noisy image for 2<CV<1 (d) proposed filter whose window size is 3×3.


50 100 150 200 250 300 350 400 450 500
100 200 300 400 500 600 700 800

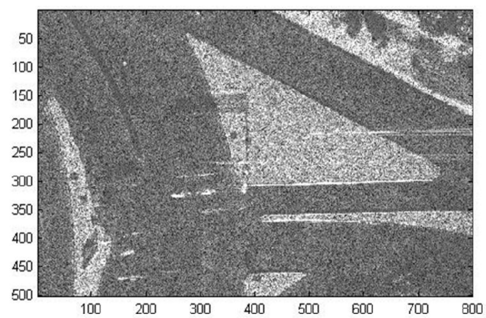
(a)


50 100 150 200 250 300 350 400 450 500
100 200 300 400 500 600 700 800

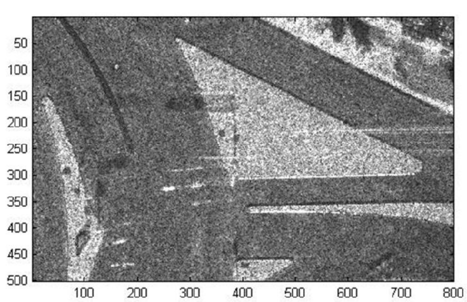
(b)


50 100 150 200 250 300 350 400 450 500
100 200 300 400 500 600 700 800

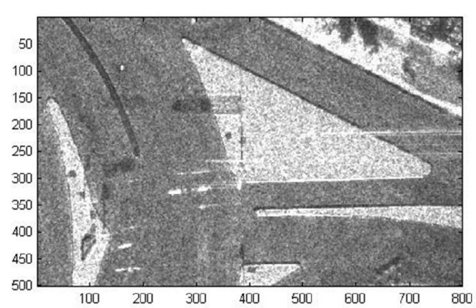
(c)


50 100 150 200 250 300 350 400 450 500
100 200 300 400 500 600 700 800

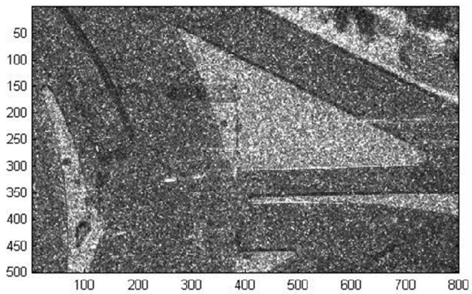
(d)

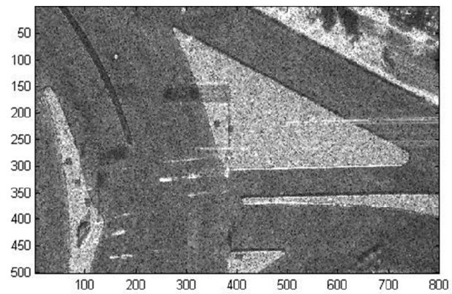

50 100 150 200 250 300 350 400 450 500
100 200 300 400 500 600 700 800

(e)

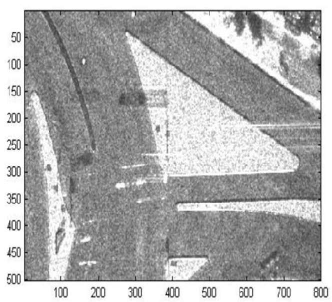

50 100 150 200 250 300 350 400 450 500
100 200 300 400 500 600 700 800

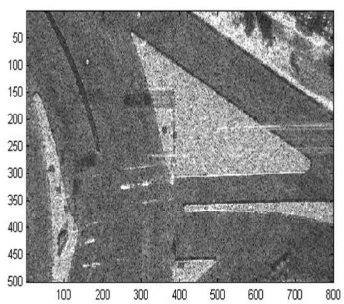
(f)

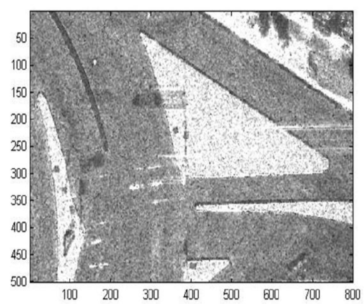




(g) (h)







(i) (j) (k)

Fig 5.4(a) original Image

(b) Fuzzy-AGK MMSE (Proposed)

(c) Fuzzy

(d) AGK-MMSE

(e) Kaun

(f) Median

(g) Lee

(h) Lee enhanced

(i) Frost

(j) Frost enhanced

(k) Gamma MAP

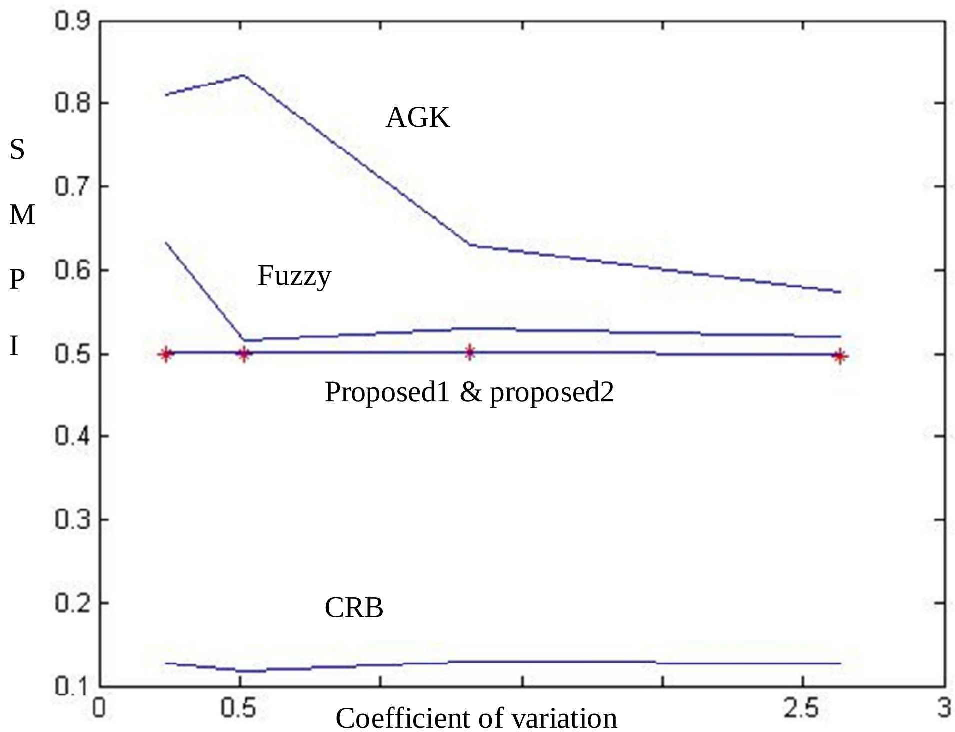


Fig. 5.5 Graph shows CRB and SMPI index for Various Filtering techniques.

The parameter index which is used to measure is SMPI (Speckle suppression and mean preservation index) and is defined now

The graph shows CRB and SMPI index for various filtering techniques. Two indices are usually used for evaluation of speckle suppression ability: ENL (Equivalent Number of Looks) and SSI (Speckle Suppression Index). These two, however, are not reliable because sometimes they overestimate mean value. Therefore, apart from ENL and SSI, we used a new index SMPI. The SMPI index can be calculated as follows

$$\boxed{\mathrm{SMPI} = \mathrm{Q} \times \frac{\sqrt{\mathrm{var}(I_f)}}{\sqrt{\mathrm{var}(I_o)}}}$$

$$\boxed{\mathrm{SSI} = \frac{\sqrt{\mathrm{var}(I_f)}}{\mathrm{mean}(I_f)} \times \frac{\mathrm{mean}(I_o)}{\sqrt{\mathrm{var}(I_o)}}}$$

where, $\mathrm{Q} = 1 + \left|\mathrm{mean}(I_f) - \mathrm{mean}(I_o)\right|$

where, I_f and I_o are filtered and noisy images.

The Results showing with other filtering techniques

Table 5.2 Results of filtering shows SSI, Mean, SMPI

Parameters	Proposed Filter-2	Proposed-1	Fuzzy filter	AGK-MMSE filter
SSI (dB)	3.7839	4.4889	17.5635	17.2908
Mean (dB)	15.2147	15.2183	15.3062	15.6132
SMPI	0.4999	0.5002	0.5144	0.8324

Table 5.3

Results of different filtering techniques showing SSI and SMPI

Filtering Techniques	SSI	SMPI
Frost	105.3523	50.6240
Gamma MAP	107.1969	35.0221
Lee	102.7010	139.2545
Lee enhanced	98.7583	40.6387
Median	105.2541	46.2593
Enhanced Frost	99.0294	38.8956
Kaun	119.7273	27.7149

SMPI and SSI shows that our proposed algorithm gives better performance than other. The parameter SSI will give speckle suppression of a image. If this index is lesser value it is good speckle suppression filter. Whereas, the parameter SMPI will give mean preservation and speckle suppression of a image. It should be minimum for better characteristic filter. However SSI cannot exactly tell the correct answer because it fails in overestimating mean.

5.7 Conclusion:

In this thesis, a new integrated Fuzzy-AGK MMSE filtering technique is developed. It preserves both edges and structure with better accuracy. For the filtered image we have found CRB for SMPI parameter and compared with other filtering techniques. Even though the SMPI index is unable to reach lower bound still it is better compared to other results. Thus we can say our modified Fuzzy-AGK gives better result and preserves edges and structure. For calculating both preserved mean and speckle suppression we have taken SMPI index not ENL (equivalent number of looks) and SSI (speckle Suppression index). The lower SMPI value has better characteristic feature.

Finally the key points are:

- With proper modulation this technique can give better result in preserving edge and structure
- This preserves good for SMPI metric and compared with other filtering techniques.
- Still there is a lot of difference between CRB and achieved SMPI parameter.

5.8 Future work

- The amount of edginess has to be found and in proportionally local statistics of a modulated kernel is varied adaptively in an image.
- Such that an ultimate approach can come from our method.

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